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An Option-Value Approach

To Technology Adoption In U.S. Manufacturing:

Evidence from Plant-Level Data

by

Adela Luque
U.C. Berkeley Ph.D. Candidate
adela@econ.berkeley.edu or aluque1@ibm.net

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ABSTRACT

Numerous empirical studies have examined the role of firm and industry heterogeneity in the decision to adopt new technologies using a Net Present Value framework. However, as suggested by the recently developed option-value theory, these studies may have overlooked the role of investment reversibility and uncertainty as important determinants of technology adoption. Using the option-value investment model as my underlying theoretical framework, I examine how these two factors affect the decision to adopt three advanced manufacturing technologies. My results support the option-value model's prediction that plants operating in industries facing higher investment reversibility and lower degrees of demand and technological uncertainty are more likely to adopt advanced manufacturing technologies.

I. INTRODUCTION

Economists have long recognized that technological change is a major determinant of productivity growth and that an important part of the process of technological change is the diffusion stage whereby new product and process innovations are put into use. Not surprisingly, numerous empirical studies have examined the adoption decision process by exploring the importance of various firm and market characteristics, using the Net Present Value model as their underlying theoretical framework. However, such models overlook the role of investment reversibility and do not address uncertainty from a formal theoretical framework — factors that Dixit (1992) and Pindyck's (1991) recently developed option-value investment theory shows to be important to investment decisions. Motivated by this theory, I examine how reversibility and uncertainty affect the likelihood of adoption of three advanced technologies in five major durable goods manufacturing industries.[1] My results support the use of this theory to analyze new technology adoption. They indicate that plants operating in industries where the degree of investment reversibility is higher and technological and demand uncertainties are lower are more likely to adopt advanced technologies.

1. Previous Empirical Studies: Standard Present Value Rule Framework

Most empirical articles on technology adoption, from the seminal work of Griliches (1957), Mansfield (1961) and Romeo (1975) to the more recent work of Hannan and McDowell (1984 and 1986), Karshenas and Stoneman (1994) and Dunne (1995), model the adoption decision either as an

[1] The technologies are Computer Numerically Controlled machines (CNC), Robotics, and Lasers. SICs 34-38 comprise Fabricated Metal Products, Industrial Machinery and Equipment, Electronics and Other Electric Equipment, Transportation Equipment and Instruments and Related Products.

explicit function of the expected returns from adopting the technology, or as a function of firm-specific and industry-specific characteristics that affect the net present value of profits from adopting it. For example, Griliches (1957) pioneering work showed that firm size and likelihood of adoption are positively correlated — a result that has been quite robust in the literature.[2] The only exception has been Oster (1982) who found firm size and likelihood of adoption to be negatively correlated in her study of the diffusion of the basic oxygen furnace in steel firms. In addition to examining firm size, Mansfield (1961, 1968) and Romeo (1975) specified the rate of diffusion of a technology as an explicit function of the industry's average rate of return from using the technology, and found that the innovation's rate of diffusion is positively correlated with the industry's average rate of return from adopting the technology.

Since then, other studies have focused on how market characteristics affect adoption. Both Hannan and McDowell (1984) and Levin, Levin and Meisel (1987) examined the role of market concentration, but obtained conflicting results. The first determined that banks operating in more concentrated markets have a higher probability of adopting ATMs, while Levin *et al*. concluded that adopters of optical scanners in the food store industry tend to operate in less concentrated markets.

Rival precedence (the proportion of market competitors that have already adopted) has also been examined as one of the factors influencing the net present value of profits from adopting a technology. Theoretical models on innovation adoption (Reinganum (1981), Quirmback (1986), Fundenberg and Tirole (1985)) suggest that rival precedence is negatively correlated with the likelihood of adoption since benefits

[2]See also Mansfield (1968), Romeo (1975), Hannan and McDowell (1984), Levin, Levin and Meisel (1987), Rose and Joskow (1990), Karshenas and Stoneman (1993) and Dunne (1994).

to the marginal adopter from acquisition decrease as the number of previous adopters increases. However, empirical studies (Mansfield (1961), Hannan and McDowell (1986), Noteboon (1993), Karshenas and Stoneman (1994)) find that there is a positive correlation between rival precedence and the probability of adoption, supporting the "epidemic effect" argument that knowledge about the technology spreads as others use it. It has been to this extent that uncertainty about the technology has been reflected in the empirical literature.

Finally, Dunne (1994) examined how a plant's age affects the decision to adopt each of seventeen advanced manufacturing technologies. A strong vintage effect would suggest that younger plants use newer, more advanced technologies. On the other hand, we would see older plants adopting newer technologies if the vintage effect is weak - and adjustment costs are low enough. His main finding is that the correlation between plant age and technology adoption is relatively weak, suggesting that there is no strong vintage effect on technology adoption.

2. Current Study: The Option-Value Investment Theory

The option-value investment theory shows that investment models relying only on the net present value rule can be in error since they do not consider three important characteristics of most investment expenditures: i) Investments may have some degree of reversibility; ii) Economic and technological environments have ongoing uncertainty and new information relevant to assessing long-run project returns arrives over time; and, iii) The investment opportunity is not likely to disappear if not taken immediately.

When these conditions hold, there is a value in waiting to invest because waiting improves the investor's chances of making the correct decision. Investment reversibility is valuable too because it allows the plant to recover some of its original investment costs if it so chooses. Since both of these values can be large, they should be taken into consideration when modeling investment decisions.

It is precisely in the context of investment in new technologies - rather than investment in more traditional equipment - that these factors are particularly relevant. The value of investment in a new technology is strongly affected by the typically high degree of uncertainty surrounding both the value and the pace of improvement of the technology. Furthermore, investment reversibility becomes especially valuable when uncertainty is high since the plant will have a chance to recoup some of the initial investment in case of a downturn.

It is primarily in this area that the present study contributes to the literature. This is one of the first empirical study that calls attention to the option-value investment theory as an appropriate theoretical framework from which to explore the decision to adopt a new technology.[3] While my empirical model is not a formalization of the option-value model, my choice of variables is guided by it, leading me to include variables that go beyond the net present value framework. In particular, I i) explore the role of investment reversibility in the technology adoption decision, and ii) call attention to the role of technological and demand uncertainties by employing two variables that have never been used before in this context: the change in patenting activity of technology *j* in industry *i*, and a set of downstream-demand indicators.

[3]Purvis, A., *et al.* (1995) examined producers' propensity to adopt free-stall dairy housing.

An additional strength of this chapter is that unlike most other studies — which focus on firms, I model the phenomenon of technology adoption at the level at which it actually occurs: the individual establishment. I use two plant-level surveys on the use of manufacturing technologies, the 1988 and the 1993 Surveys of Manufacturing Technology, and also the 1982 and 1987 Census of Manufactures to obtain additional plant-level and industry-specific characteristics. Because these data do not constitute a panel and do not indicate when the technology was adopted or how long the plant has been using it, I am unable to employ a hazard rate model, as some fairly recent technology adoption papers have (e.g., Hannan and McDowell (1986), Karshenas and Stoneman (1993)). However, by estimating a qualitative choice model for each of the technologies in both 1988 and 1993, I am able to observe the magnitude and significance of the estimated coefficients, and see how the effects of the variables under consideration have changed over time. That is, I look at two points in the diffusion curve, rather than the pattern of diffusion.

The structure of this chapter is as follows. The next section introduces Dixit and Pindyck's option-value investment model. Section III follows with a description of the empirical methodology and the data that I use. Section IV presents a detailed account of the variables and what their expected effect should be according to the theory. In Section V, I present the results, and finally I conclude in Section VI.

II. THEORETICAL FRAMEWORK[4]: THE OPTION-VALUE MODEL

An opportunity to invest is a "call option": a chance to buy an asset at some price within a specific period of time. To invest is to exercise the option. If uncertainty about the future has a sufficiently large

[4]This section is based on Dixit and Pindyck (1998).

downside, the option to invest has a holding value (i.e., a value of waiting to invest). This is because under uncertainty, the passage of time provides the plant with new information about the desirability and value of the investment project. The plant invests only if the latest information about the value of the project deems the project valuable enough;[5] that is, when the Net Present Value of the investment is large enough to offset the value of continuing to wait. Therefore, when uncertainty exists, waiting has a value and the plant will be less likely to invest.[6]

Investment reversibility (i.e., the option to disinvest) gives rise to a "put option"; a chance to sell an asset at some price within a given time period. Under uncertainty, the plant that has the opportunity to partially or totally disinvest under adverse conditions will be more likely to invest than a plant that does not have the opportunity to disinvest. In other words, if the downside of uncertainty about the future is large enough, holding a put option will make the plant more willing to invest now.

Dixit and Pindyck model the problem of a firm facing uncertainty and holding an investment opportunity (i.e., a call option) that has to decide when to exercise it while also considering whether it holds a put option (i.e., a chance to disinvest under adverse conditions). Uncertainty is modeled by having the value of the investment follow a stochastic process. In reality, the value of the investment may depend on uncertain future prices of output and inputs, uncertain technological conditions (e.g., uncertainty about the rate of technological change of a given technology), strategic considerations, etc. For ease of exposition,

[5]Sometimes, though, strategic considerations void the (call) option of any holding value and make it imperative for the plant to invest quickly.

[6]As it has traditionally been indicated, waiting also has an (opportunity) cost. As I will show later in this section, Dixit and Pindyck also take this opportunity cost into consideration in modeling the investment decision.

I present uncertainty as demand uncertainty. However, any type of uncertainty regarding the value of the project can be shown to have the same qualitative effect in the investment decision.[7]

Since there is no analytical solution for the case where the plant can reverse some of its initial investment cost and can also hold the option to invest open, I present the theory's predictions case-by-case. First I describe the case where the investment cannot be reversed, but the plant can hold the investment opportunity open. Second, I present some numerical solutions of the general case where the investment is (partially) reversible and the plant can hold the investment opportunity open.

Assume that the plant faces a demand curve defined by:

$$P = \theta(t)Q^{-1/\eta} \qquad (1)$$

where η is the elasticity of demand and the shift parameter, θ, varies stochastically according to a geometric brownian motion:

$$d\theta = \alpha\theta dt + \sigma\theta dz \qquad (2)$$

[7]In their most general model, Dixit and Pindyck solve the problem of a firm that must decide when to invest in a single project that requires a sunk cost, I, and has a value, V, that is stochastic. V evolves according to a geometric Brownian motion with a non-zero trend growth α, and a proportional variance per unit time, σ: $dV = \alpha V dt + \sigma V dz$ where σ represents uncertainty. They arrive at the rule that maximizes the value of the option to invest, F(V). This investment rule takes the form of a critical value V* such that it is optimal to invest once V > V*:

$$V^* = \frac{\beta_1}{\beta_1 - 1} I$$

where $\beta_1 = \frac{1}{2} - (\rho-\delta)/\sigma^2 + \{[(\rho-\delta)/\sigma^2 - 1/2]^2 + 2\rho/\sigma^2\}^{1/2} > 1$, and δ is defined as the difference between ρ and α. Since β_1 is >1, $\beta_1/(\beta_1 - 1) > 1$ and V* >I. Notice that the NPV rule is V*=I; that is, the optimal investment threshold is lower under the NPV rule.

where the expected value of *d*è, E[dè]=áè*dt*, and áè is referred to as the expected instantaneous drift rate. The variance of *d*è, V[*d*è]=(óè)^2*dt* and (óè)^2 is referred to as the instantaneous variance rate.

The plant can invest at a cost k(t) = k$_0$e^{ñt} per unit. The parameter ñ captures the plant's option to invest; that is, the plant's opportunity for future investment. As ñ moves away from 0 and towards 4, the value of the call option (the plant's opportunity to purchase capital at a later date) is reduced, and therefore, the plant will be more likely to exercise the option (i.e., invest).

The plant can sell installed capital for a price S(t) = k$_1$e^{-st} per unit. The parameter *s* captures the degree of reversibility of installed capital. If *s* = 0, then capital investment is completely reversible and the plant can recuperate the entire sunk cost. As *s* 64, the plant is able to recoup less and less of the initial investment cost (i.e., investment becomes less and less reversible), and the value of the put option will be reduced. As the option to disinvest disappears, the incentive to invest diminishes.

To determine when to invest, the plant must consider the value of investing: the expected profitability from the investment plus the resale price if the investment is reversible. Given the value of the investment, it must consider the value of the holding the option to invest (i.e., the value of waiting). Let ÎV represent the value of the last unit of installed capital which has two components: the expected profitability from the use of the unit plus the value of the option to sell the unit. ÎF represents the value of the option to add one more unit.

In order to determine the value of ÎV and ÎF, and then arrive at the optimal investment threshold, Dixit and Pindyck use finance option pricing to construct two riskless portfolios, each involving ÎV and ÎF independently.[8] By equating each riskless portfolio to the riskless rate of return, they obtain two differential equations, one for ΔF and another for ΔV.

ΔF has to satisfy:

$$\frac{1}{2}\sigma^2\theta^2\Delta F_{\theta\theta}+(r-\delta)\theta\Delta F_{\theta}+\Delta F_t-r\Delta F = 0 \qquad (3)$$

where r is the risk-free rate of return and δ is the rate-of-return shortfall defined by the difference between some risk-adjusted rate of return, µ, and α (the rate at which θ grows).

Subject to the following boundary conditions:[9]

$$\Delta F(K;0,t)=0 \qquad (4)$$

$$\Delta F(K;\theta^*,t)=\Delta V(K;\theta^*,t)-k_0e^{\rho t} \qquad (5)$$

$$\Delta F_{\theta}(K;\theta^*,t)=\Delta V_{\theta}(K;\theta^*,t) \qquad (6)$$

$$\lim_{t\to\infty}\Delta F(K;\theta,t)=0 \qquad (7)$$

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[8]The solution to the problem can be arrived at either via dynamic programming or via finance contingent claim methods. The contingent claim method requires the assumption that there is an asset or one can construct a dynamic portfolio of assets that is perfectly correlated with θ.

[9]Equation (4) says that as the value of the call option goes to zero, it will stay at zero. Equation (5) is the value-matching condition; it says that the value of ΔF and ΔV have to be the same at the optimal investment threshold. Upon investing, the plant receives a payoff of ΔV minus the initial investment cost. Equation (6) is the smooth-pasting condition; it says that the slopes of ΔF and ΔV must equal each other at the optimal investment threshold. If ΔF and ΔV were not continuous and smooth at the optimal exercise point, we could do better by exercising at a different point. Equation (7) says that as time goes to infinity, the value of the call option approaches zero.

ΔV must satisfy:

$$\frac{1}{2}\sigma^2\theta^2\Delta V_{\theta\theta}+(r-\delta)\theta\Delta V_{\theta}+\Delta V_t-r\Delta V+\left(\frac{\eta-1}{\eta}\right)\theta K^{-1/\eta} = 0 \tag{8}$$

subject to the following boundary conditions:[10]

$$\lim_{\theta\to\infty}\Delta V = \left(\frac{\eta-1}{\eta\delta}\right)K^{-1/\eta}\theta \tag{9}$$

$$\Delta V(K;\theta^{**},t) = \Delta F(K;\theta^{**},t)+k_0 e^{-st} \tag{10}$$

$$\Delta V_{\theta}(K;\theta^{**},t) = \Delta F_{\theta}(K;\theta^{**},t) \tag{11}$$

Irreversibility & Option to Invest is Open

In this case the plant cannot disinvest ($s = \infty$), therefore ΔV becomes the present value of future profits from the incremental unit of capital:

$$\Delta V = \frac{(\eta-1)}{\eta\delta}K^{-1/\eta}\theta = \omega(K)\theta \tag{12}$$

Once ΔV is valued, the solution for ΔF is:

$$\Delta F = a(K)\theta^{\beta_1}e^{-gt} \tag{13}$$

[10]Equation (9) says that as the value of the unit of installed capital increases, the plant will never want to sell the unit, so its value is just the present value of expected profit flows. Equations (10) and (11) are the matching-value and smooth-pasting conditions.

and using the boundary conditions, the critical investment rule is:

$$\theta^{*}(K,t) = \frac{\beta_1}{(\beta_1 - 1)} \frac{\eta\delta}{(\eta - 1)} K^{1/\eta} k_0 e^{\rho t} \tag{14}$$

where,

$$\beta_1 = \frac{1}{2} - \frac{(r-\delta)}{\sigma^2} + \sqrt{[(r-\delta)/\sigma^2 - \frac{1}{2}]^2 + 2(r+g)/\sigma^2} \quad > 1 \tag{15}$$

$$g = \rho[-\frac{1}{2} - \frac{(r-\delta-\rho)}{\sigma^2} + \sqrt{[\frac{(r-\delta-\rho)}{\sigma^2} + \frac{1}{2}]^2 + \frac{2\delta}{\sigma^2}} \quad] \quad > 0 \tag{16}$$

As uncertainty, σ, increases, β_1 increases which implies that the investment threshold becomes higher and the plant is more likely to postpone investment. In other words, as uncertainty is higher, the value of the call option increases, waiting to invest becomes more valuable and investment is less likely.

As the opportunity for future investment decreases (i.e., as ρ increases), $\beta_1/(\beta_1-1)$ goes to infinity and ΔF becomes zero for t>0 and max[0, $\omega(K)\theta$ - k_0] for t=0. In words, ΔF is either zero or the net present value of the incremental investment; that is, there is no option to invest after t=0. This particular case occurs whenever the option to invest is limited. For instance, strategic considerations regarding industry competitors or potential entrants can make it too costly for the plant to postpone investment and make it imperative for the plant to invest now. Other examples include the need for a permit or license in short supply, or limited natural resources, etc. Although this model does not explicitly account for these scenarios, they are reflected in future higher costs of investment (i.e., an increase in ρ).

General Case: Partial Reversibility and Option to Invest is Open

The general case where ρ and s are both positive and finite (i.e., the plant has an option to invest and the investment is partially reversible) can be resolved analytically if the investment and disinvestment thresholds are far enough apart that the two sets of boundary conditions are independent of each other. Dixit and Pindyck show that the solutions to equations (3) and (8) are of the form:

$$\Delta F = A(K)\theta^{\beta_1} e^{-gt} \tag{17}$$

$$\Delta V = B(K)\theta^{\beta_2} e^{-ht} + \left(\frac{\eta - 1}{\eta\delta}\right) K^{-1/\eta}\theta \tag{18}$$

with β_1 and g are given by equations (15) and (16), and analogously β_2 and h are:[11]

$$\beta_2 = \frac{1}{2} - \frac{(r-\delta)}{\sigma^2} + \sqrt{[(r-\delta)/\sigma^2 - \frac{1}{2}]^2 + 2(r+h)/\sigma^2} \quad < \ 0 \tag{19}$$

$$h = s[-\frac{1}{2} - \frac{(r-\delta-s)}{\sigma^2} + \sqrt{[\frac{(r-\delta-s)}{\sigma^2} + \frac{1}{2}]^2 + \frac{2\delta}{\sigma^2}}\ ] \quad > \ s \tag{20}$$

[11] β_2 and h are obtained in the same fashion as β_1 and s, but from solving the problem when the investment is completely reversible and there is no option to invest.

and the investment threshold conditions can be found numerically using the boundary conditions (5) and (6), which after making some substitutions become:

$$A(K)(\theta^*)^{\beta_1}e^{-gt} = B(K)(\theta^*)^{\beta_2}e^{-ht} + \omega(K)\theta^* - k_0 e^{\rho t} \tag{21}$$

$$\beta_1 A(K)(\theta^*)^{\beta_1 - 1}e^{-gt} = \beta_2 B(K)(\theta^*)^{\beta_2 - 1}e^{-ht} + \omega(K) \tag{22}$$

These two equations can be solved numerically for the investment threshold for given parameter values and values for K and t. Before I show some numerical results, it is worth noticing that compared to the irreversible case in (12), ΔV in (18) has an additional term, $B(K)\theta^{\beta_2}e^{-ht}$, which is nonnegative. This means that the value of an additional unit of capital is always greater when the unit can be resold. The investment is reversible and the put option has value making it more appealing for the plant to invest. Of course, the value of this term and its effect on the incentive to invest will depend on the value of other parameters such as r, δ, etc. We can see this by examining Table 1 which shows the numerical results for the investment threshold as the opportunity to invest ρ and the degree of irreversibility s vary.

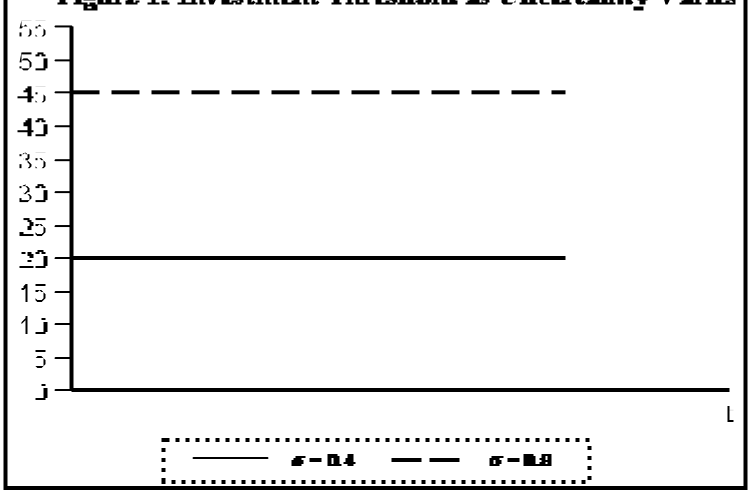
Table 1
Investment Threshold as ρ and s vary

	s			
ρ	**0.0**	**0.2**	**0.4**	**0.6**
0.0	6.586	6.716	6.716	6.716
0.2	3.073	3.144	3.144	3.144
0.4	2.469	2.528	2.528	2.528

Parameters: $r=\delta=0.05$, $\sigma=0.4$, $\eta=1.2$, $k_p=3$, $k_r=1$

These results point out that, holding everything else constant, as the opportunity to invest is reduced (i.e., as ñ increases), the value of the call option decreases, and therefore, the optimal investment threshold is lower and investment postponement is unlikely since the value of waiting to invest disappears. Table 1 also shows that keeping everything else constant, the more irreversible an investment is (as *s* increases), the value of the put option decreases, and therefore, the more unlikely the plant will invest since disinvestment becomes impossible under adverse conditions.

Figure 1: Investment Threshold as Uncertainty Varies



For the same parameter values as in Table 1 above, Figure 1 illustrates the numerical results for the investment threshold as the degree of uncertainty varies. In general, increases in uncertainty, σ, will raise the value of holding the investment opportunity. This is the case because the investment opportunity is a call option and the greater the volatility of the value of the project, the greater the value of this call option (i.e., holding the opportunity to invest open).

III. EMPIRICAL METHODOLOGY AND DATA

1. Estimation

I employ a probit model to estimate the probability of adopting a new technology as a function of reversibility and uncertainty as well as of other variables that control for plant and market characteristics.[12] That is:

$$Pr_{ij}(t) = f(X_{it},T_{ht},Z_{jht}) \quad ,$$

where:

$Pr_{ij}(t)$ = probability that plant *i* adopts technology *j* by time *t*, *i* = plant, *j* = technology, *h* = industry, and *t* = time.

Table 2 below classifies the variables in my model. It denotes which variables have been included in previous studies and which ones are unique to my analysis. For the later group, it separate them into those motivated by the option-value model, and those that are not.

Table 2: Variable Classification

		Plant Level X_i	**Industry Level T_h**	**Technology-Industry Level Z_{jh}**
Used in previous studies		• Size • Age • Fabrication vs Assembly Dummy	• 4-firm Concentration Ratio	
Not used in previous	Non Option-Value Variables	• Capital-Labor Ratio		
studies	Option-		• Degree of Reversibility	• Technological Uncertainty

[12] I use Maximum Likelihood to estimate the probability that a plant will adopt.

In the option-value context, a plant will adopt if at any time *t*, its investment value "index", $è_{ij,}$ (a function of the independent variables above) is at least as great as the optimal investment value threshold, $è_{ij}*$. Assume that the difference between $è_{ij}$ and $è_{ij}*$ is $Y_{ij}*$. Then,

Plant *i* adopts, $Y_{ij}=1$ if $è_{ij} \$ è_{ij}*$ or $Y_{ij}* \$ 0$,

Plant *i* does not adopt, $Y_{ij}=0$ if $è_{ij} < è_{ij}*$ or $Y_{ij}* < 0$,

Pr (adoption) = $\Pr(Y_{ij}=1) = \Pr(Y_{ij}* \$ 0) = \Pr(â' X + u_i > 0) =$

$\Pr(u_i \$ -â' X) = 1 - F(-â' X)$

where $\Pr(Y_{ij} = 1)$ is the probability that plant *i* will adopt technology *j*, â' is the vector of parameters to be estimated, u_i is the error term, F(.) is the cumulative normal function and X is the vector of independent variables.

I estimate the model at two points in time, 1988 and 1993. As I mentioned earlier, this allows me to observe the magnitude and significance of the estimated coefficients although due to data limitations, my analysis is constrained to the examination of two points on the diffusion path as opposed to an estimation of the diffusion curve itself.

2. Data

For my variable construction and model estimation, I link a variety of data sets. I employ two different plant-level U.S. Census Bureau data sets: the 1988 and 1993 Survey of Manufacturing

Technology (SMT) and the 1982 and 1987 Census of Manufactures (CM). In 1988 and 1992, the SMT surveyed approximately 10,000 manufacturing plants about the use of 17 separate technologies. In addition to data on technology usage, the survey also contains information on plant age, industry, product market, defense contracting status and ownership. The CM is a survey conducted every five years that covers the entire universe of manufacturers in the U.S. and provides information on sales, capital expenditures, employment, payroll, legal form of organization and inventories.

The three advanced manufacturing technologies I examine are: numerically controlled or computer numerically controlled machines (CNC), material working Lasers, and Robots. (See Appendix A for a list and brief description of these technologies, and Appendix B for each technology's percentage of adoption by 2-digit industry.) The industries under examination are those included in major industry groups 34 - Fabricated Metal Products, 35 -Nonelectrical Machinery, 36 - Electric and Electronic Equipment, 37 - Transportation Equipment, and 38 - Instruments and Related Products. The data from the SMT allow me to identify which advanced manufacturing technologies a manufacturing plant utilizes and provides critical microdata for plant age as well as for the nature of manufacturing taking place in the plant. The CM supplies the data for the construction of the reversibility variable (i.e., 3-digit industry expenditures on new and used equipment), plant size, the plant-level capital-labor ratio and the industry-level four-firm concentration ratios.

I also employ data from the United States Patent and Trademark Office (USPTO) patent data base and Micropatent Database to construct the patenting activity variables. The Micropatent Database provides an annual account of patents which includes a description of the patent, the International Patent Classes

(IPC) to which it has been assigned by the examiner, the year of patent application, the name of the inventor, and citations of previous patents to which this particular patent may be related.

Finally, in the construction of the demand uncertainty variable, I use the Bartelsman, Caballero and Lyons (1994) 4-digit downstream demand indicators as updated by Baily, Bartelsman and Haltiwanger (1998). The data contains downstream demand indicators along with their respective 4-digit industry from 1978 to 1994.[13]

IV. DETERMINANTS OF TECHNOLOGY ADOPTION: DESCRIPTION OF VARIABLES

1. Uncertainty, s

I proxy for two different types of uncertainty: demand uncertainty and technological uncertainty.

Demand Uncertainty

As I mentioned above, I create a measure of demand volatility, DV_{ht}, specific to the 4-digit industry to which the plant is assigned by using the downstream activity indicator constructed by Bartelsman, Caballero and Lyons (1994) as updated by Baily, Bartelsman and Haltiwanger (1998). The BCL downstream indicator is a weighted average of changes in economic activity (measured by cost-share weighted aggregate of factor inputs) of other industries and services sectors, with weights equal to their share of purchases of the output from the industry in question.

[13]These data reside at the Center for Economic Studies, Bureau of the Census.

Baily *et al*. update these indicators according to Shea's (1993) relevance and exogeneity criteria. Relevance is satisfied when the downstream industry purchases intermediate inputs that comprise a large portion of the upstream industry's output. This criteria is met by the BCL indicator by construction since they are weighted averages of activity in all (exogenous) downstream industries. Exogeneity is satisfied when the purchases from the upstream industry constitute only a small fraction of total material expenditures of the downstream industry. Baily *et al*. filter out downstream sectors which fail to meet the exogeneity criteria.[14] I use downstream demand indicators instead of variance of sales because the first isolates demand fluctuations while the latter responds not only to demand shocks, but also to technology shocks affecting industry productivity and growth.

I then construct a measure of demand volatility, DV_{ht}, by taking the deviation of the updated downstream demand indicator described above from the linear time trend, and then, taking the variance of those deviations.[15] I use deviations from the trend because I do not want to attribute a high variance to high industry growth given that I am attempting to capture (unexpected) demand volatility. Following the option-value theory's predictions, I expect to find a negative correlation between my measure of demand volatility, DV_{ht}, and the likelihood of adoption.

Technological Uncertainty

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[14]They exclude from the BCL downstream indicator for each industry those downstream industries whose purchases of the upstream industry are larger than 5 percent of their expenditures on intermediate inputs.

[15]Alternatively I employed an autorregressive trend instead of a linear one. Regression results are qualitatively the same.

Plants may also face uncertainty about future improvements in technology. In the option-value framework, Dixit and Pindyck (1994, pg. 167) and Farzin, Huisman and Kort (1998) show that a faster rate of innovation arrival compels the firm to postpone adoption. Rosenberg (1976) also argued that the optimal timing of adopting an innovation "becomes heavily influenced by expectations concerning the timing and the significance of future improvements", and that "a firm may be unwilling to introduce the new technology if it seems highly probable that further technological improvements will shortly be forthcoming." Thus, a plant may postpone the adoption of a technology if it considers the rate of technological change of that technology in its industry to be high.

The percentage change in the number of patents in technology *j* assigned to industry *h* between periods *t* and *t-1* may signal a plant in that industry about that technology's rate of change in the near future.[16] Algebraically, I define this proxy variable as:[17]

$$\Delta P_{jh_{t-(t-1)}} = \frac{NP_{jht} - NP_{jh(t-1)}}{(NP_{jht} + NP_{jh(t-1)})/2} \quad ,$$

where NP_{jht} is the number of patents in technology *j* assigned to industry *h* in period *t*.

[16]For this chapter, patents are assigned to the industry where the patented innovation on the technology is likely to be used, and not manufactured. That is, I assign it to its SIC of Use. The reason for doing this is twofold. One, I am interested in technological uncertainty of technology users, and two, I am interested in industry-level effects and particular patents may have an impact far beyond the boundaries of the industry they originate.

[17]In practice the derivation of this variable is more involved than its conceptual representation. Patents in the U.S. are not assigned to SICs. I rely on Brian Silverman's methodology to assign a patent to a given SIC. 'The Concordance' provides a linkage between U.S. SIC and Canada's SIC codes. Also, the Canadian patent data provides the mapping between International Patent Classes and Canadian SICs. By using these two "cross-walks", the algorithm assigns a given patent (i.e., International Patent Class) to a given U.S. SIC.

I expect the change in patenting activity and likelihood of adoption to be inversely related if the downside of the uncertainty associated with adopting now is sufficiently large. That is, a increase in patenting activity over time may signal the plant that future improvements are likely, and therefore, the plant will be less likely to invest.

On the other hand, strategic considerations may compel a plant to invest now rather than later. As I mentioned earlier, Dixit and Pindyck show that under uncertainty, the ability to keep the opportunity to invest open, ñ, gives rise to a "call option". However, sometimes the opportunity cost of not investing may be very high and the call option may rapidly lose value in industries where the pace of technological change is rapid since plants in these industries may consider that waiting to invest will put it technologically behind its competitors. If this 'strategic considerations' effect dominates, ÄP$_{jh\,t-(t-1)}$ would carry a sign opposite to the one suggested by the technological uncertainty argument.

2. Reversibility, s

To the best of my knowledge, this is the first empirical study that attempts to obtain a cross-sectional measure of capital reversibility. Ideally one would like to construct a measure of reversibility that reflects a technology's retention of value — how much of its original value it retains after some length of time. For example, a ratio of prices of used to new equipment at the plant, firm or industry level would provide a fair proxy of how much of the initial investment a plant could expect to recuperate if it decided to sell the technology at a later date.

However, the price data necessary to construct such a variable are not available. Thus, I construct a proxy that relies on the industry-specificity of capital to measure how equipment investment reversibility varies across industries.[18] The proxy measures the level of activity in an industry's production equipment resale market, and I define it as the ratio of 3-digit SIC-level capital expenditures on used machinery over 3-digit SIC-level total (both old and new) expenditures in machinery:[19]

$$R_{ht} = \frac{U_{ht}}{U_{ht} + N_{ht}} \qquad ,$$

where U_{ht} is industry *h*'s capital expenditures on used machinery at time *t* and N_{ht} is industry *h*'s capital expenditures on new machinery.

Assuming that capital is largely industry specific, an industry's relative used capital expenditures will be highly correlated with the industry's sales of used capital. One can then argue that the more active the equipment resale market is, the more reversible investment in a technology is in that industry, and therefore, the more likely it is that a plant will invest in the technology.[20]

3. Industry Characteristics

Concentration Ratios

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[18]The idea of industry-specificity of capital is well established (for example, see Bernanke (1983), Dixit & Pindyck (1993), Abel *et al.* (1996)), and has been documented by Ramey and Shapiro (1998).

[19]The reason for using 3-digit SIC is Ramey and Shapiro's (1998) evidence that equipment tends to be resold within the 3-digit SIC level and that that equipment that is resold outside its industry of origin tends to lose a high proportion of its resale value.

[20]Ideally, I would like to have used and new expenditures on the technology in particular.

Neither the theoretical nor the empirical literature offer unambiguous predictions for the relationship between market structure and innovation-related investment. On the theoretical side, Schumpeter argues that firms with monopoly power should be more inclined to engage in innovation because their incentive to do so is higher and/or because they have the financial resources to do so. Continuing in this idea, Reinganum (1981) shows that increases in the number of firms in a market delays adoption of a cost-reducing, capital-embodied process innovation. On the other hand, a firm presently realizing monopoly profits may be less motivated to seek additional profits than the one earning only normal profits. Baldwin and Childs (1969) have argued that a firm with monopoly power is in an advantageous position to be a "fast second" in the development of an innovation. Because of its resources and established reputation and channels of distribution, a firm with monopoly power can afford to wait until someone else innovates and imitate it quickly if it appears to be successful.

I use the proxy most widely used to reflect market structure: 4-firm market concentration ratios. However, one must exercise caution when interpreting the role of market concentration (or any other market structure variable) since a high concentration ratio may be indicative of monopoly power or may reflect the underlying production technology in the industry rather than monopoly power.

4. Plant Characteristics

Capital-Labor Ratio

The inclusion of capital-labor ratios as a control for plant heterogeneity is motivated by Olley and Pakes' (1996) model of unobserved producer heterogeneity. This model predicts that efficient firms generate higher levels of investment and larger capital stocks. Thus, in this context "capital intensity may act as a proxy for other unobserved sources of efficiency."[21] Capital intensity is defined as:

$$\frac{K_i}{L_i},$$

where K_i is the book value (in thousand of dollars) of machinery capital in plant *i* and L_i is the number of production workers in plant *i*.[22]

Nature of Manufacturing

I also control for whether the plant performs fabrication or only assembly. Certain plants may be more likely to adopt certain technologies simply because of the type of work performed in them. For example, a plant that only performs assembly is not likely to adopt a technology that is primarily used in fabrication (such as lasers). The dummy equals one if the plant carries out any fabrication, and equals zero if it just conducts assembly.

Size

As I mentioned earlier, the empirical evidence on the effect of size on technology adoption has been quite robust and indicates that there is a positive correlation between size and likelihood of adoption. Several explanations have been offered for why this is so. David (1975) suggests that the larger the size,

[21]Doms *et al.* (1994) are the first ones to employ this line of argument.

[22]The book value of capital is used in place of physical capital since physical capital is not available. Doms (1996) constructs capital based o the perpetual-inventory method and compares this series with the book value series. The correlation between the two series is above .90. Thus, the reported book values should act as a reasonable proxy for the physical capital stock.

the greater the output over which to spread the equipment fixed costs of a capital-embodied innovation. Another explanation emphasizes that the costs of learning and putting into use the technology are also fixed costs which will be spread more thinly as output increases; therefore, larger plants will have a cost advantage, and thus, will be more likely to adopt the technology. In the present chapter, the size variable is represented by the log of plant employment.

Age

The effect of plant age on technology adoption is not clear. On the one hand, one might expect younger plants to have higher rates of technology adoption because they have the opportunity to choose the newest available technology. On the other hand, Dunne (1991) points out that it is possible that plant survival is positively correlated with adoption. This would skew the observed distribution of surviving (i.e., older) plants toward plants that have already adopted. Furthermore, it is not clear how strong the vintage effect is. For instance, in Pakes and Ericson's (1998) model, existing firms are able to retool their plants (i.e., update their technologies) and, therefore, the vintage effect is predicted to be relatively weak. On the other hand, in his industry evolution model without active learning, Lambson (1991) predicts a strong vintage effect by showing that existing plants have a harder time switching to the new technology — while within an entry cohort, one may find some entrants adopting new technologies and others adopting standard technology. The plant age variable consists of dummy variables representing three age categories: less than or equal to 15 years, sixteen to thirty years and more than thirty years respectively.

V. RESULTS

Tables 1a, 1b, 2a and 2b present the probit regression results for 1988 and 1993. For each year, Tables 1a and 2a show the results for the specification where the size and age variables are not interacted, while tables 1b and 2b display the interacted size and age dummies. In addition, tables 1c, 1d, 2c and 2d present the marginal effects of the respective probit estimations. Each column in the tables corresponds to one of the three manufacturing technologies under examination. For each technology, I also include the results of the specification without the reversibility and uncertainty variables.

1. Uncertainty and Reversibility Variables

Demand Uncertainty

I consider demand variations over the ten-year period prior to the plant-level observation. That is, in the 1988 estimation DV_{ht} measures demand volatility in the period from 1978 to 1987, while in the 1993 probit DV_{ht} covers the years 1983 through 1992. In general, the results for this variable support the option-value theory's prediction that demand volatility and the likelihood of adoption are negatively correlated. All of the significant coefficients are negative, and with the exception of robotics, all of the technologies have a significant negative coefficient for this variable in one or both years' regressions.

Change in Patenting

In the 1988 cross-section, ÄP$_{jht-(t-1)}$ measures the change in patenting activity between the 1978-82 and 1983-87. While in the 1993 estimation, the difference is between the patenting activity in the 1983-87 and 1988-92 periods. In general I find that there is a negative correlation between ÄP$_{jht-(t-1)}$ and likelihood of adoption although the results vary somewhat by technology and cross-section. In the 1993 cross-section the coefficients for all technologies are negative, although only CNCs is significant. In the

1988 probit, CNC, Robots and Lasers are negative. These results are consistent with the idea — put forth by Rosenberg (1976) and Dixit and Pindyck (1994) among others — that a increase in patenting activity over the time period *t* and *t-1* signals the plant that a future improvement in the technology is probable making the plant less likely to invest now in the new technology.

Reversibility

In order to minimize simultaneity as well as business cyclicality effects, I use the average of the 1977, 1982 industry-level ratios in the 1988 probit, and the 1977, 1982, 1987 average in the 1993 probit. I do this for all technologies except for Lasers, where I use the 1987 ratio since a resale market for this technology did not develop until the mid 1980s.

In general the results suggest that R_{ht} is positively correlated to likelihood of adoption: all significant coefficients are positive. In the 1988 cross-section, the coefficients for CNCs, and Robots are positive, indicating that for these technologies, plants in industries that have a more active resale market for production equipment are more likely to invest in new technologies. In 1993, the coefficients for CNCs, and Robots are still positive and significant. Laser technology has a negative, insignificant coefficient in both cross-sections. This could be due to the fact that Lasers are a newer technology than the others, and that their resale market did not fully developed until the early 1990s.[23]

In order to test the hypothesis of whether the reversibility and uncertainty variables contribute significantly to the technology adoption decision, I perform a Likelihood Ratio (LR) test for each technology

[24]Ideally I would like to know how the ratio I use varies not only across industries, but also across technologies. This would reduce the measurement error in this variable.

in 1988 and 1993. The results from these tests indicate that in both cross-sections and for all technologies, the degree of investment reversibility and of demand and technological uncertainties are significant factors in determining the decision to adopt.

2. Market, Firm and Plant Characteristics

Concentration Ratio

The results in both the 1988 and 1993 probits indicate that for most technologies, the concentration ratio coefficients are positive and significant when the reversibility and uncertainty proxies are included in the regression. However, I also find that the coefficients for laser technology are positive but not significant, and that those of CNC are negative and significant. This seems to indicate that the role of market concentration is dependent upon the technology under examination, and thus, is consistent with both Hannan and McDowell's (1984, 1986) and Karshenas and Stoneman's (1994) findings.

Size and Age

As in most of the empirical articles that examine the effect of size on technology adoption, my results indicate that the correlation between plant size and the likelihood of adoption is positive and significant. That is, the bigger a plant is, the higher the probability that the plant will adopt a technology. The positive correlation between plant size and likelihood of adoption is consistent across technologies as well as across time. The coefficients of the log of plant employment are positive and highly significant, especially for bigger plants.

The results indicate that the correlation between age and likelihood of adoption varies by year and tends to be negative although not always significant. In the 1988 cross-section the age coefficient of the oldest plants is negative and significant for CNC technologies, as well as for Robots in the full specification. In the 1993 cross-section, the age-adoption correlation is negative and significant for Lasers and Robots.

In the interactive age-size model, and interesting pattern emerges. Small, young plants are more likely to adopt relative to small, old plants. After a certain employment threshold, the size effect overwhelms the age effect. Figures 2 through 7 in Appendix C illustrate the point by plotting for each technology, the predicted probability of adoption as a function of employment size for the three age classes. This pattern is actually consistent with two hypotheses of how age may affect technology adoption. It supports Pakes and Ericson's (1998) active learning model where existing (older) plants are able to retool and update their technologies. It is also compatible with the argument made by Dunne (1991) that one might expect younger plants to have higher rates of technology adoption because they have the opportunity to choose the newest available technology.

Capital-Labor Ratio

The capital-labor ratio coefficients for all technologies and in both cross-sections are mostly positive indicating that capital intensive plants are more likely to invest in new technologies. However, while in the 1993 probit, the coefficients are always significant, in the 1988 probit, none of the three technologies has a significant coefficient.[24] If, as suggested by Olley and Pakes (1996), this ratio proxies for unobserved

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[25]I use 1982 data for the 1988 probit (and 1987 data for the 1993 probit) to minimize endogeneity to the extent possible.

sources of efficiency, the results that I obtain seem to indicate that plants that are more efficient are also more likely to adopt.

VI. CONCLUSION

My results support the idea that investment reversibility and uncertainty are important factors to consider when modeling plants' technology adoption decisions. For example, I found that investment reversibility as proxied by the ratio of industry-level used to total equipment expenditures is in general positively correlated with the likelihood of adoption, and that demand uncertainty is negatively correlated with the likelihood of adoption. Technological uncertainty was likewise negatively correlated with new technology use, though these results varied somewhat by technology and year. This variation may have been a result of my change in patenting activity variable also proxying for strategic considerations. That is, a plant in an industry with rapid technological change may be compelled to invest in a new technology if it believes that failure to do so will place it at a competitive disadvantage.

Including variables that proxy uncertainty and investment reversibility does not overturn previous findings regarding the traditionally examined firm and market heterogeneity variables. In particular, size remains the dominant determinant of adoption behavior.

The interaction between plant size and age was intriguing. The only previous empirical article that addressed the relationship between plant age and the likelihood of adoption was Dunne (1994). He found that the effect of age on the likelihood of adoption is weak. While my results do not contradict his, they indicate that age may have an important role depending on plant size: small, young plants seem more likely to adopt than small, old plants. This result deserves further attention.

Table 1a: 1988 Probit Regression Results

Dependent Variable=1 if plant has adopted

	CNC		LASERS		ROBOTS	
Constant	-2.347 *	-2.321 *	-3.521 *	-3.639 *	-3.855 *	-3.637*
	(0.080)	(0.072)	(0.132)	(0.126)	(0.111)	(0.098)
Plant Characteristics						
Log of 1982 Total Employment	0.340 *	0.337 *	0.331 *	0.333 *	0.481 *	0.470*
	(0.012)	(0.012)	(0.018)	(0.018)	(0.015)	(0.015)
15<Age88<=30	-0.070 *	-0.064	-0.163 *	-0.169 *	-0.089	-0.071
	(0.036)	(0.037)	(0.060)	(0.060)	(0.045)	(0.045)
Age88 > 30	-0.112 *	-0.112 *	-0.092	-0.111	-0.107 *	-0.075
	(0.039)	(0.039)	(0.061)	(0.060)	(0.048)	(0.047)
Fabrication Dummy	1.089 *	1.096 *	0.275 *	0.252 *	0.013	0.052
	(0.045)	(0.044)	(0.068)	(0.067)	(0.049)	(0.049)
Capital-Labor 1982 ratio	0.0002	0.001	0.009	0.009	0.009	0.009
($000/worker)	(0.012)	(0.012)	(0.011)	(0.011)	(0.011)	(0.011)
Market Characteristics						
4-firm Concentration Ratio,1982	-0.378 *	-0.415 *	0.219	0.179	0.737 *	0.704*
	(0.079)	(0.077)	(0.120)	(0.119)	(0.094)	(0.092)
Uncertainty						
Downstream Demand Indicator, 1978-87	-0.130 *		-0.264 *		0.149	
	(0.065)		(0.106)		(0.077)	
Change in patenting 78-82 to 83-87	-0.085 *		-0.008		-0.039	
	(0.018)		(0.022)		(0.021)	
Reversibility						
Used machinery share in industry 77,82	0.828 *		-0.517		1.490 *	
	(0.341)		(0.347)		(0.411)	
Log Likelihood	-4798.01	-4820.37	-1771.64	-1776.47	-3136.31	-3149.78
Number of obs	8097	8097	8067	8067	8039	8039

(Standard Errors in Parenthesis)
* Implies Significance at the 0.05 level.

Table 1b: 1988 Probit Regression Results, Interactive Age-Size

Dependent Variable=1 if plant has adopted

	CNC		LASERS		ROBOTS	
Constant	-1.929 *	-1.906 *	-2.970 *	-3.095 *	-3.381 *	-3.167 *
	(0.101)	(0.095)	(0.170)	(0.165)	(0.141)	(0.131)
Plant Characteristics						
15<Age88<=30	-0.482 *	-0.486 *	-1.150 *	-1.160 *	-0.912 *	-0.875 *
	(0.131)	(0.131)	(0.240)	(0.240)	(0.188)	(0.187)
Age88>30	-1.083 *	-1.069 *	-0.891 *	-0.891 *	-0.844 *	-0.813 *
	(0.140)	(0.139)	(0.222)	(0.222)	(0.186)	(0.186)
Log of Plant Employment in 1982	0.246 *	0.244 *	0.218 *	0.220 *	0.382 *	0.371 *
	(0.019)	(0.019)	(0.029)	(0.029)	(0.024)	(0.024)
15<Age88<=30*Log of Plant Employment	0.098 *	0.100 *	0.193 *	0.193 *	0.166 *	0.162 *
	(0.028)	(0.028)	(0.044)	(0.044)	(0.036)	(0.036)
Age88>30*Log of Plant Employment	0.206 *	0.203 *	0.156 *	0.153 *	0.146 *	0.146 *
	(0.028)	(0.028)	(0.040)	(0.040)	(0.034)	(0.034)
Fabrication Dummy	1.075 *	1.082 *	0.267 *	0.245 *	0.009	0.049
	(0.045)	(0.044)	(0.068)	(0.067)	(0.049)	(0.049)
Capital-Labor 1982 ratio ($000/worker)	-0.002	-0.001	0.007	0.007	0.008	0.008
	(0.012)	(0.012)	(0.011)	(0.011)	(0.011)	(0.011)
Market Characteristic						
4-firm Concentration	-0.411 *	-0.451 *	0.190	0.150	0.717 *	0.683 *
Ratio,1982	(0.079)	(0.078)	(0.121)	(0.120)	(0.094)	(0.093)
Uncertainty						
Downstream Demand Indicator, 1978-87	-0.143 *		-0.271 *		0.147	
	(0.065)		(0.107)		(0.077)	
Change in patenting	-0.084 *		-0.011		-0.039	
78-82 to 83-87	(0.018)		(0.022)		(0.021)	
Reversibility						
Used machinery share in industry 77, 82	0.857 *		-0.499		1.518 *	
	(0.342)		(0.348)		(0.411)	

Log Likelihood	-4771.06	-4793.94	-1759.9	-1764.9	-3122.8	-3136.5
Number of obs	8097	8097	8067	8067	8039	8039

(Standard Errors in Parenthesis)
* Implies Significance at the 0.05 level

Table 1c: 1988-82 Probit Regression Marginal Effects

	CNC	LASERS	ROBOTS
Plant Characteristics			
Log of 1982 Plant Employment	0.1355*	0.0331*	0.1103*
15<Age88<=30	-0.0280*	-0.0155*	-0.0200
Age88 > 30	-0.0448*	-0.0089*	-0.0240*
Fabrication Dummy	0.3897*	0.0238*	0.0029
Capital-Labor 1982 ratio ($000/worker)	0.0001	0.0331	0.0021
Market Characteristic			
4-firm Concentration Ratio,1982	-0.1506*	0.0219	0.1691*
Uncertainty			
Downstream Demand Indicator, 1978-87	-0.0519*	-0.0264*	0.0342
Change in patenting 78-82 to 83-87	-0.0337*	-0.0008	-0.0090
Reversibility			
Used machinery share in industry 77,82	0.3303*	-0.0516	0.3418*

Marginal Effects evaluated at mean values for continuous variables
Discrete change of dummy variables from 0 to 1
* Implies Significance at the 0.05 level

Table 1d: 1988 Interactive Age-Size Probit Regression Marginal Effects

	CNC	LASERS	ROBOTS
Plant Characteristics			
15<Age88<=30	-0.1896*	-0.0895*	-0.1771*
Age88 > 30	-0.4028*	-0.0696*	-0.1626*
Log of 1982 Plant Employment	0.0981*	0.0216*	0.0880*

15<Age88<=30*Log of Plant Employment	0.0391*	0.0191*	0.0382*
Age88 > 30*Log of Plant Employment	0.0821*	0.0155*	0.0336*
Fabrication Dummy	0.3868*	0.0230*	0.0021*
Capital-Labor 1982 ratio ($000/worker)	-0.0009	0.0007	0.0018
Market Characteristic			
4-firm Concentration Ratio,1982	-0.1639*	0.0189	0.1654*
Uncertainty			
Downstream Demand Indicator, 1978-87	-0.0572*	-0.0269*	0.0339
Change in patenting 78-82 to 83-87	-0.0335*	-0.0011	-0.0090
Reversibility			
Used machinery share in industry 77,82	0.3418*	-0.0496	0.3499*

Marginal Effects evaluated at mean values for continuous variables
Discrete change of dummy variables from 0 to 1
* Implies Significance at the 0.05 level

Table 2a: 1993-87 Probit Regression Results

Dependent Variable=1 if plant has adopted

	CNC		LASERS		ROBOTS	
Constant	-2.226 *	-2.135 *	-3.774 *	-3.859 *	-3.747 *	-3.565 *
	(0.093)	(0.084)	(0.149)	(0.144)	(0.119)	(0.107)
Plant Characteristics						
Log of 1987 Plant Employment	0.308 *	0.301 *	0.367 *	0.368 *	0.504 *	0.493 *
	(0.014)	(0.014)	(0.020)	(0.020)	(0.017)	(0.017)
15<Age93<=30	-0.039	-0.033	-0.121	-0.130 *	-0.187 *	-0.172 *
	(0.042)	(0.042)	(0.064)	(0.064)	(0.050)	(0.050)
Age93 > 30	-0.002	0.017	-0.165 *	-0.182 *	-0.252 *	-0.222 *
	(0.045)	(0.044)	(0.066)	(0.066)	(0.053)	(0.052)
Fabrication Dummy	1.168 *	1.202 *	0.394 *	0.380 *	0.041	0.079
	(0.050)	(0.049)	(0.075)	(0.075)	(0.054)	(0.053)
Capital-Labor 1987 ratio ($000/worker)	0.033	0.039	0.064 *	0.069 *	0.086 *	0.088 *
	(0.025)	(0.025)	(0.032)	(0.031)	(0.027)	(0.026)
Market Characteristic						
4-firm Concentration Ratio,1987	-0.609 *	-0.532 *	0.247	0.146	0.633 *	0.621 *
	(0.093)	(0.088)	(0.131)	(0.128)	(0.105)	(0.102)
Uncertainty						
Downstream Demand Indicator, 1983-92	-0.036		-0.452 *		0.132	
	(0.084)		(0.142)		(0.098)	

	CNC		LASERS		ROBOTS	
Change in patenting 83-87 to 88-92	-0.126 *		-0.022		-0.019	
	(0.019)		(0.025)		(0.021)	
Reversibility						
Used machinery share in industry 82, 87	1.636 *		-0.197		1.541 *	
	(0.436)		(0.370)		(0.516)	
Log Likelihood	-3636.79	-3661.36	-1535.28	-1541.00	-2606.70	-2613.34
Number of obs	6273	6273	6273	6273	6273	6273

(Standard Errors in Parenthesis)
* Implies Significance at the 0.05 level

Table 2b: 1993-87 Regression Results, Interactive Age-Size

Dependent Variable=1 if plant has adopted

	CNC		LASERS		ROBOTS	
Constant	-1.989 *	-1.914 *	-3.546 *	-3.619 *	-3.575 *	-3.406 *
	(0.117)	(0.111)	(0.199)	(0.195)	(0.157)	(0.149)
Plant Characteristics						
15<Age93<=30	-0.380 *	-0.340 *	-0.128	-0.160	-0.494 *	-0.456 *
	(0.154)	(0.153)	(0.259)	(0.258)	(0.216)	(0.215)
Age93>30	-0.449 *	-0.399 *	-0.851 *	-0.878 *	-0.520 *	-0.449 *
	(0.154)	(0.153)	(0.266)	(0.265)	(0.210)	(0.209)
Log of Plant Employment in 1987	0.253 *	0.251 *	0.320 *	0.318 *	0.468 *	0.459 *
	(0.022)	(0.022)	(0.034)	(0.034)	(0.028)	(0.028)
15<Age93<=30*Log of Plant Employment	0.078 *	0.070 *	0.006	0.011	0.062	0.057
	(0.032)	(0.032)	0.048	(0.048)	0.041	(0.041)
Age93>30*Log of Plant Employment	0.096 *	0.090 *	0.121 *	0.123 *	0.053	0.045
	0.031	(0.031)	0.046	(0.046)	(0.039)	(0.038)
Fabrication Dummy	1.165 *	1.199 *	0.390 *	0.375 *	0.041	0.079
	0.050	(0.049)	(0.075)	(0.074)	(0.054)	(0.053)

Capital-Labor 1987 ratio ($000/worker)	0.032	0.039	0.063 *	0.070 *	0.085 *	0.088 *
	(0.025)	(0.025)	0.032	(0.031)	(0.027)	(0.026)
Market Characteristic						
4-firm Concentration Ratio,1987	-0.626 *	-0.548 *	0.230	0.126	0.628 *	0.612 *
	(0.093)	(0.088)	(0.131)	(0.128)	(0.105)	(0.102)
Uncertainty						
Downstream Demand Indicator, 1983-92	-0.030		-0.451 *		0.138	
	(0.085)		(0.143)		0.098	
Change in patenting 83-87 to 88-92	-0.128 *		-0.022		-0.019	
	(0.019)		(0.025)		(0.021)	
Reversibility						
Used machinery share in industry 77,82,87	1.669 *		-0.177		1.567 *	
	(0.436)		(0.371)		(0.517)	
Log Likelihood	-3631.36	-3660.15	-1530.91	-1537.37	-2605.33	-2615.11
Number of obs	6273	6273	6273	6273	6273	6273

(Standard Errors in Parenthesis)
* Implies Significance at the 0.05 level

Table 2c: 1993-87 Probit Regression Marginal Effects

	CNC	LASERS	ROBOTS
Plant Characteristics			
Log of 1987 Plant Employment	0.1221*	0.0412*	0.1273*
15<Age93<=30	-0.0153	-0.0131	-0.0457*
Age93 > 30	-0.0008	-0.0177*	-0.0608*
Fabrication Dummy	0.4281*	0.0364*	0.0102
Capital-Labor 1987 ratio ($000/worker)	0.0131	0.0071*	0.0216*
Market Characteristic			
4-firm Concentration Ratio,1987	-0.2415*	0.0277	0.1596*
Uncertainty			
Downstream Demand Indicator, 1983-92	-0.0144	-0.0507*	0.0334

Change in patenting 83-87 to 88-92	-0.0498*	-0.0025	-0.0049
Reversibility			
Used machinery share in industry 77, 82, 87	0.6485*	-0.0221	0.3887*

Marginal Effects evaluated at mean values for continuous variables
Discrete change of dummy variables from 0 to 1
* Implies Significance at the 0.05 level

Table 2d: 1993-87 Interactive Size-Age Probit Regression Marginal Effects

	CNC	LASERS	ROBOTS
Plant Characteristics			
15<Age93<=30	-0.1507*	-0.0139	-0.1139*
Age93 > 30	-0.1776*	-0.0777*	-0.1192*
Log of 1987 Plant Employment	0.1004*	0.0360*	0.1182*
15<Age93<=30*Log of Plant Employment	0.0308*	0.0007	0.0156
Age93 > 30*Log of Plant Employment	0.0382*	0.0136*	0.0133
Fabrication Dummy	0.4274*	0.0363*	0.0103
Capital-Labor 1987 ratio ($000/worker)	0.0127	0.0071*	0.0215*
Market Characteristic			
4-firm Concentration Ratio,1987	-0.2481*	0.0258	0.1587*
Uncertainty			
Downstream Demand Indicator, 1983-92	-0.0120	-0.0508*	0.0348
Change in patenting 83-87 to 88-92	-0.0507*	-0.0025	0.0049
Reversibility			
Used machinery share in industry 77, 82, 87	0.6613*	-0.0200	0.3961*

Marginal Effects evaluated at mean values for continuous variables
Discrete change of dummy variables from 0 to 1
* Implies Significance at the 0.05 level

Appendix A:

Description of Technologies[1]

[1]Source: *Current Industrial Reports: Manufacturing Technology 1988, U.S. Bureau of the Census.*

Numerically Controlled Machines/Computer Numerically Controlled Machines
NC machines are controlled by numerical commands punched on paper or plastic mylar tape while CNC machines are controlled through an internal computer.

Materials Working Lasers
Laser technology used for welding, cutting, treating, scrubbing and marking.

Pick/Place Robot
A simple robot with 1-3 degrees of freedom, which transfer items from place to place.

Other Robots
A reprogrammable, multifunctioned manipulator designed to move materials, parts, tools or specialized devices through variable programmed motions.

Appendix B:

Number & Percentage of Technology Adopters By Year & 2-digit Industry

SIC2	YEAR	CNC		LASER		ROBOT	
34		**Number**	**%**	**Number**	**%**	**Number**	**%**
	1988	843	10.41%	83	1.03%	336	4.18%
	1993	773	12.32%	93	1.48%	293	4.67%
35							
	1988	1430	17.66%	138	1.71%	391	4.86%
	1993	1200	19.13%	124	1.98%	315	5.02%
36							
	1988	693	8.56%	161	2.00%	430	5.35%
	1993	599	9.55%	138	2.20%	406	6.47%
37							
	1988	563	6.95%	93	1.15%	235	2.92%
	1993	475	7.57%	80	1.28%	187	2.98%
38							
	1988	523	6.46%	92	1.14%	201	2.50%
	1993	380	6.06%	91	1.45%	183	2.92%
Adopters Total	1988	4052	50.42%	567	7.05%	1593	19.82%
	1993	3427	54.63%	526	8.39%	1384	22.06%
Sample Total	1988	8097		8067		8039	
	1993	6273		6273		6273	

Appendix C:

Predicted Probabilities by Technology in 1988 and 1993

Figure 2

Figure 3

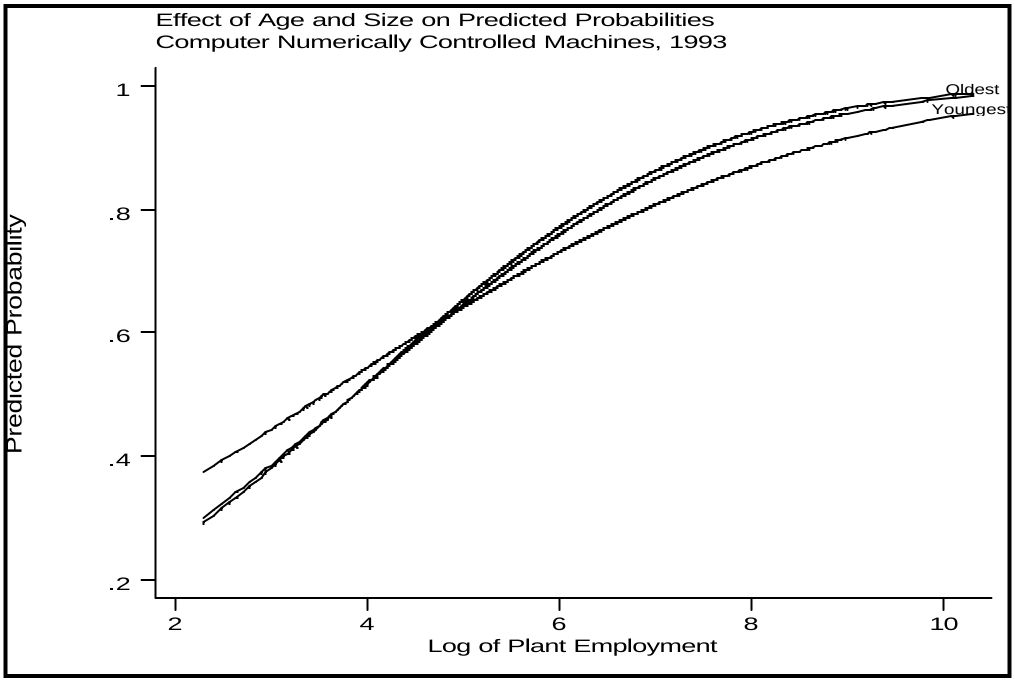


Figure 4

Figure 5

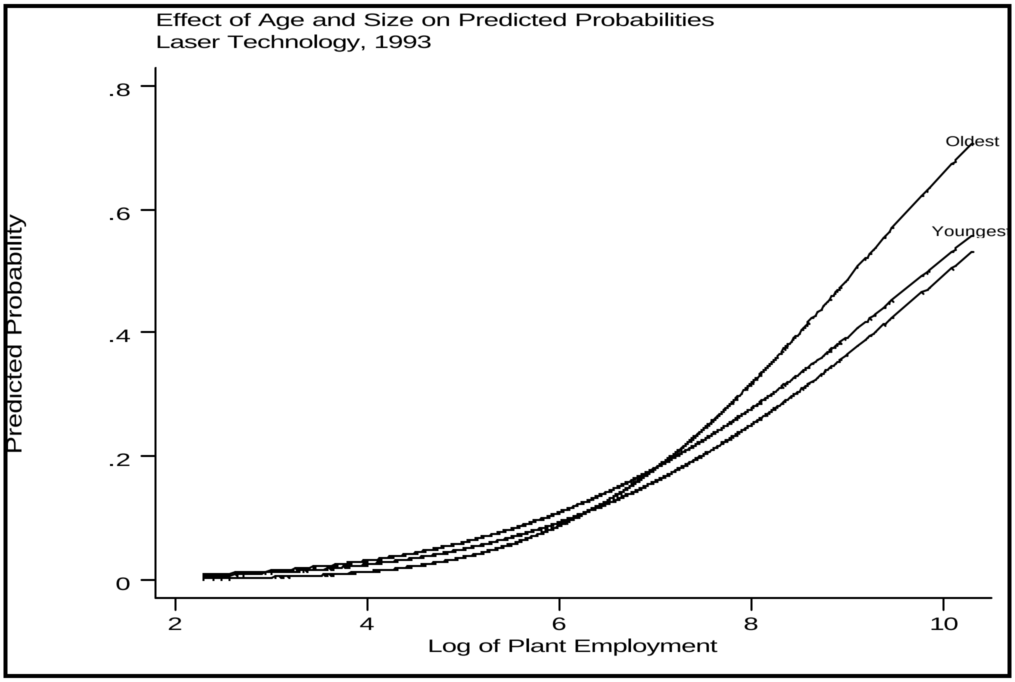
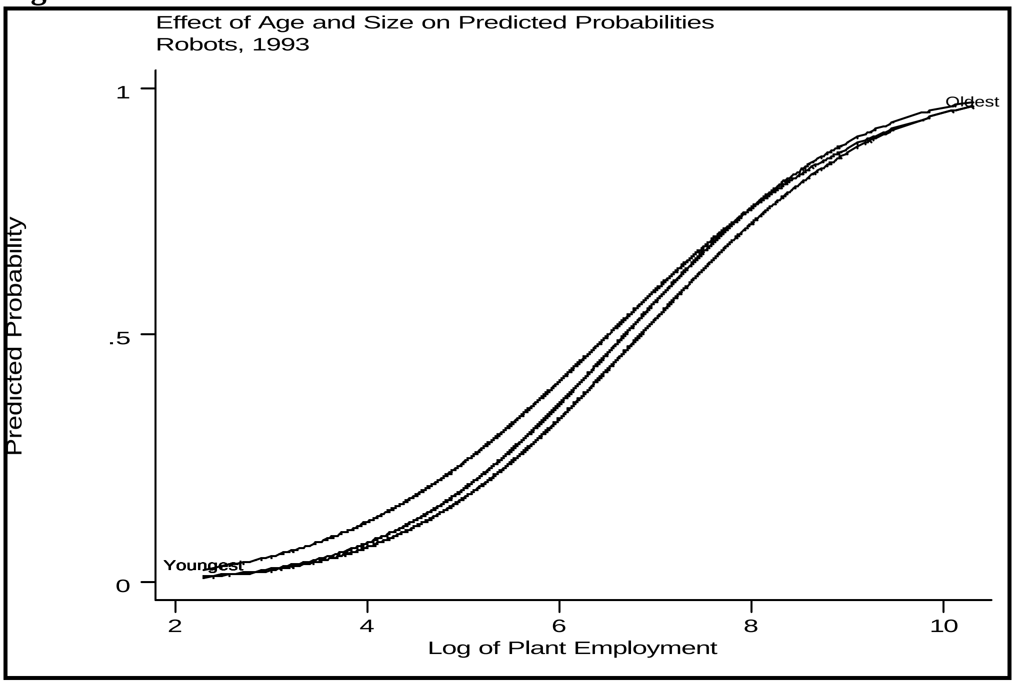

Effect of Age and Size on Predicted Probabilities
Laser Technology, 1993
Predicted Probability
.8
.6
.4
.2
0
Oldest
Youngest
2
4
6
8
10
Log of Plant Employment

Figure 6


Effect of Age and Size on Predicted Probabilities
Robots, 1988
Predicted Probability
1
.5
0
Oldest
Youngest
2
4
6
8
10
Log of Plant Employment

Figure 7



Effect of Age and Size on Predicted Probabilities
Robots, 1993
Predicted Probability
1
.5
0
Oldest
Youngest
2
4
6
8
10
Log of Plant Employment

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